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Research Article

Simultaneous Application of Intensive Sensing and Sleep Scheduling to Increase the Lifetime of Wireless Sensor Network using Collective Intelligence

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Abstract

One of the primary challenges in wireless sensor networks is the limited energy of nodes and their lifespan. In this paper, we utilize compressive sensing theory to reduce the number of transmissions and ultimately increase the lifespan of the wireless sensor network. The data in some wireless sensor networks, in addition to spatial correlation, also has temporal correlation. The proposed method in this paper exploits both types of correlation to minimize the mean squared error of the reconstructed data signal. Additionally, we employ a sleep/wake algorithm to reduce the energy consumption of nodes. The awake nodes in the proposed method are determined using a genetic algorithm, as finding the optimal nodes is an NP-hard problem. After deciding the awake nodes, an ant colony algorithm is used to construct the optimal aggregation tree for the awake nodes. Simulation results show that our proposed approach in selecting awake nodes and routing them leads to an improvement of more than 48% in reconstruction error and also an increase of more than 18% in network lifetime compared to the evaluated methods.

Keywords: Wireless sensor network, intensive sensing theory, sleep-wake algorithm, data aggregation routing, energy consumption, lifetime.

Highlights

- Choosing awake nodes intelligently, which will improve the reconstruction accuracy and increase the lifetime of the network compared to when the sensor nodes are randomly activated.
- The reduction of reconstruction error in the proposed method is due to the use of a genetic algorithm to find awake nodes.
- The longer lifetime of the node is due to the intelligent selection of awake nodes with the genetic algorithm, and by considering the remaining energy of the sensors and using optimal routing with the ant algorithm.

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1. Introduction

In recent years, with significant advancements in the technology of manufacturing high-performance, appropriately sized sensors with wireless communication capabilities, the possibility of utilizing wireless sensor networks for monitoring physical phenomena in various applications has been made possible. For instance, water quality monitoring [1], agricultural monitoring [2], forest fire monitoring [3], and so on.

One of the primary challenges in such networks is the limited energy of the sensor node, which manifests as a weakness in performance. Numerous solutions have been proposed to reduce energy consumption and extend the lifespan of the sensor network. One of these solutions is the employment of compressive sensing. Compressive sensing [4] provides a novel perspective for efficient data collection without compromising data recovery quality. This method enables the base station, which essentially serves as the fusion center, to reconstruct physical phenomena using a smaller volume of data.

2. Innovation and contributions

In this research, the focus is on conventional wireless sensor networks, which consist of a vast number of sensor nodes densely distributed in the field. These types of networks are utilized for gathering data of interest in applications such as geographic monitoring, industrial surveillance, security, and climate monitoring. In the data of sensor networks for physical phenomena, there is spatial correlation as well as temporal correlation. Given that the data signal changes very little in each round due to high temporal correlation [6,7], the proposed approach, by utilizing the information of the reconstructed signal in the previous round, first selects the awake nodes in the next round at the base station using a genetic algorithm, and then constructs an optimal Steiner tree using an ant colony algorithm to connect the awake nodes to each other and to the base station. The intelligent selection of awake nodes will improve the reconstruction accuracy and increase the network lifetime compared to when sensor nodes are activated randomly [5, 8, 9].

Among the innovations of this paper, the following can be stated:

In the proposed method, after identifying the awake nodes, a compressed sensory data aggregation tree must be optimally constructed to send the data of the awake nodes to the base station. The awake nodes, as terminals, must be included in the tree. However, in most cases, the tree cannot be constructed only with terminals, and additional nodes must also participate in the tree construction. The problem of constructing such a tree is the Steiner tree problem, which is an NP-Hard problem.

We have utilized the ant colony optimization algorithm for tree construction. Initially, we place an ant at each terminal node, which must be connected to each other. In each iteration, the ant moves to one of the neighboring sensor nodes. The selection of the next node is entirely random, but in a way that ants are attracted to the paths traversed by others. Each ant maintains a separate list of nodes it has previously visited, referred to as the taboo list. This list prevents the ant from revisiting a node it has already encountered. When an ant encounters another ant or even the path of another ant, it joins it so that the paths followed by the two ants form a common subtree. When all ants reach the base station, a Steiner tree is constructed in each iteration based on their paths.

The tree constructed at this stage is initially used to send control packets to the nodes that should participate in the desired round. Each node that receives a control packet identifies its parent and children in the tree and waits to receive them. Then, this same tree will also be used to send compressed sensory data by the awake nodes.

The reconstruction error in our proposed method is lower than other methods. The reason for the reduction in reconstruction error compared to other methods is the use of a genetic algorithm to find awake nodes.

Our proposed method outperforms other tested methods in terms of lifespan. The reason for the superior performance of the proposed method is the intelligent selection of awake nodes using a genetic algorithm, considering the remaining energy of the sensors, as well as the use of optimal routing with an ant colony algorithm.

3. Materials and Methods

In this section, we demonstrate using synthetic data that the proposed method outperforms other methods in terms of signal reconstruction accuracy and network lifetime. The simulations were conducted using the MATLAB programming environment.

To evaluate energy consumption, the model presented in [11] is employed. The sensor radio operates in one of four states: transmitting, receiving, listening (active), or sleeping.

Table 1 shows the power consumption of each state and the required time. The formula for energy and power is $\text{Energy} = \text{Power} \times \text{Time}$.

For example, the amount of energy consumed by a transmitter to send a data packet can be calculated using the following equation:

$$\text{Energy} = \text{Power} \times \text{Time}$$

$$\text{Energy} = P_t \times \text{Time}$$

$$\text{Energy} = P_t \times L \times T_B$$

$$\text{Energy} = 60 \times 24 \times 0.416 \times 10^{-3}$$

$$\text{Energy} = 0.00059904 \text{ J} \approx 599 \mu\text{J}$$

All data and control packets are assumed to be 64 bits long. An AWGN channel is used for sensor transmissions, resulting in various data loss probabilities. We employ the CVX software package [12] for reconstructing the compressed sensor signal. The reconstruction performance is evaluated using the mean relative error $\frac{\|x\|_2^2}{\|\hat{x}-x\|_2^2}$.

Network lifetime is defined as the time when the first sensor dies. In order to evaluate the performance, we compared the proposed method with method [5] which only utilizes spatial correlation, method [10] which utilizes both spatial and temporal correlation, and the proposed method in [9] which uses a model-free Q-learning algorithm for searching optimal decision-making strategies while simultaneously employing a compressed sensor and sleep scheduling.

In the simulations, n wireless sensor nodes are randomly distributed in a square environment with dimensions $d \times d \text{ m}^2$. The communication radius of the sensors is considered to be R meters. The base station is also located at one of the corners of the environment at coordinates $(0, 0)$. The initial energy of all sensor nodes is E_{int} . The data signal x is randomly generated with a dimension of n for different time instants, where s non-zero components are selected independently and identically distributed (i.i.d.) from a Gaussian distribution with zero mean and unit variance. The dictionary Ψ is initially constructed by creating an $n \times n$ matrix with i.i.d. selections from a Gaussian distribution $N(0,1)$, and then the columns of Ψ are normalized to a unit scale. The wireless channel SNR is considered to be 20 dB, which along with the modulation type and packet length, determines the data loss probability [13].

A value of $\beta = 10^{-3}$ was considered. Additionally, sensor measurements were subjected to zero-mean Gaussian noise errors, resulting in a signal-to-noise ratio of 20 dB. Furthermore, it was assumed in all experiments that 20% of the estimated signal was inaccurate.

In the ant colony algorithm simulation, a population size of 50 and 100 iterations were considered. Additionally, the parameter values were set to $\rho = 0.1$, $\gamma = 5$, $\lambda = 2$, $\alpha = 1$, $\beta = 1.5$.

4. Results and Discussion

Figure 1 illustrates the reconstruction accuracy for the proposed method and the methods presented in [5] and [10] for different values of s . The value of m is considered to be 200. As can be seen, for all methods, the reconstruction error decreases with decreasing s . The reconstruction error in our proposed method is lower than the other methods. The proposed method resulted in approximately a 48% improvement in reconstruction error compared to method [5]. The reason for the decrease in the reconstruction error is the selection of appropriate nodes to send data in each round, while the selection of awake nodes in [5] is completely random. Compared to the method in [10], we have about a 59% improvement in reconstruction error, which is due to the use of a genetic algorithm to find awake nodes. In [10], as mentioned earlier, the problem is solved by using convex reconstruction with simplification, and the solutions of the genetic algorithm are more optimal than the convex reconstruction method. The proposed method in [9] is a distributed method and cannot find suitable awake nodes that lead to a lower relative error and results in a suboptimal shadow matrix. Therefore, the reconstruction error of this method is also higher than our proposed method. Our proposed algorithm reduces the reconstruction error by about 61% compared to this method.

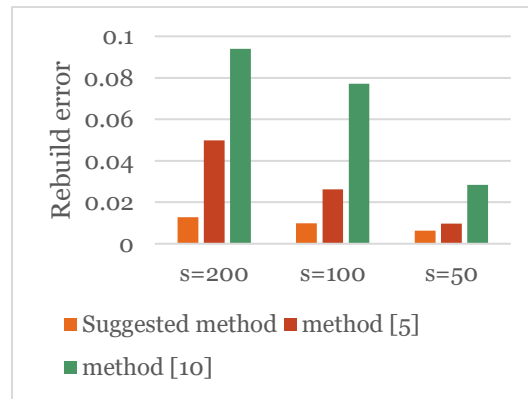


Figure 1: Reconstruction error of different methods for various sparsity level

In Figure 2, we evaluate the network lifetime for the proposed method as well as two other methods, where $s=100$. This figure illustrates the network lifetime for different values of m , representing the number of active nodes in each round. The proposed method outperforms both other methods in terms of lifetime. The superior performance of the proposed method is attributed to the intelligent selection of active nodes using a genetic algorithm, considering the residual energy of sensors, and the employment of optimal routing using an ant colony algorithm.

The proposed method in [9] has a relatively similar lifespan compared to our method. The reason for the good lifespan of the method in [9] is the distributed nature of their algorithm and the reduction in the overhead of sending control packets.

Our proposed method, compared to the method presented in [5], has led to an average improvement in network lifetime of about 18%. When compared to the method proposed in [10], this improvement is approximately 32%, and in comparison to method [9], it has resulted in a nearly 1% increase in network lifetime.

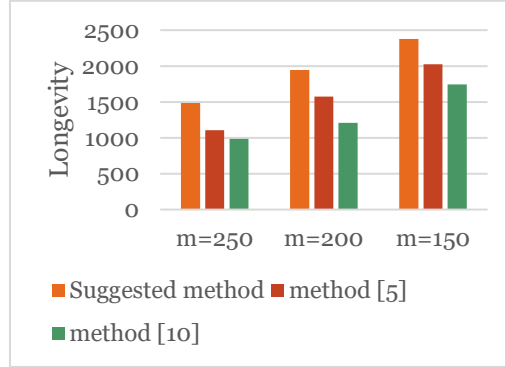


Figure 2: Network lifetime versus the number of awake nodes

In Figure 3, we also evaluate the reconstruction error for different simulation methods with varying values of m . For these experiments, we set $s=100$. In all evaluated methods, the reconstruction error decreases as the number of awake nodes in each round increases.

Even in this form, it is clearly evident that the reconstruction error of the proposed method is better than the two evaluated methods, the reasons for which superiority were previously explained.

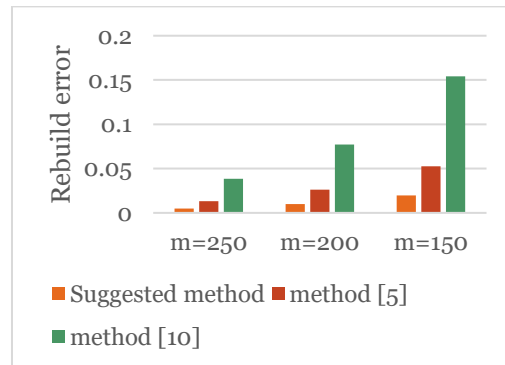


Figure 3: Reconstruction error as a function of the number of awake nodes

In sensor networks, both the signal accuracy of the received data and the network's lifetime are of paramount importance. Figure 4 simultaneously examines both the lifetime and reconstruction error parameters in the form of $P = \frac{\text{Longevity}}{\text{error} \times 10^4}$ for various values of m and s in the proposed method to determine the optimal value of m .

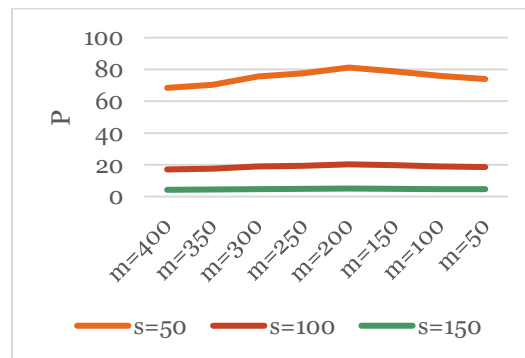


Figure 4: Simultaneous investigation of lifetime and accuracy for different numbers of awake nodes

The higher the value of m , representing the number of active nodes in each phase, the lower the reconstruction error; however, the network lifetime decreases. For the conducted experiments, $m=200$ was found to be the optimal number of active nodes.

As a final test and evaluation of the overall performance of all four methods, we have simultaneously examined both the lifetime parameter and the reconstruction error under the parameter $P = \frac{\text{Parameter length}}{\text{error} \times 10^4}$. In this experiment, the value of $m=200$ was considered.

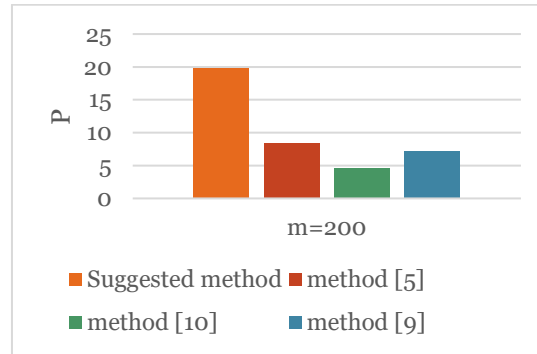


Figure 5: A simultaneous examination of the lifespan and accuracy of the evaluation methods

As illustrated, our proposed method outperforms all three compared methods when considering both network lifetime and reconstruction error simultaneously. The reasons for this superiority have been elaborated in the preceding sections.

5. Conclusion

In order to increase the lifetime of wireless sensor networks, compressed sensing can be utilized. When employing compressed sensing, some nodes participate in data transmission while others do not. Nodes that do not participate in data transmission can be put into sleep mode to save energy. Random and distributed selection of awake nodes leads to a higher reconstruction error; therefore, a centralized method was used for node selection. In the proposed method, the awake nodes were determined using a genetic algorithm. Additionally, an ant colony optimization algorithm was used to construct an optimal path between the awake nodes and the base station. Simulation results indicate an increase in lifetime and a decrease in reconstruction error by employing the proposed method.

In the proposed method, a relationship was used to identify awake nodes. In this relationship, the previous round data signal was used. In future work, we will utilize a predictor to construct the next round signal based on the temporal correlation between the sensor data signals. This constructed signal will then be incorporated into the relationship to better identify the awake nodes.

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